A Wearable Nutrition Monitoring System

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***Abstract*—Maintaining appropriate levels of food intake and developing regularity in eating habits is crucial to weight loss and the preservation of a healthy lifestyle. Moreover, maintaining awareness of one's own eating habits is an important step towards portion control and ultimately, weight loss. Though many solutions have been proposed in the area of physical activity monitoring, few works attempt to monitor an individual's food intake by means of a noninvasive, wearable platform. In this paper, we introduce a novel nutrition-intake monitoring system based around a wearable, mobile, wireless-enabled necklace featuring an embedded piezoelectric sensor. We also propose a framework capable of estimating volume of meals, identifying long-term trends in eating habits, and providing classification between solid foods and liquids with an F-Measure of 85% and 86% respectively. The data is presented to the user in the form of a mobile application.**

***Index Terms*—Piezoelectric sensor; Wireless Health; Nutrition; Necklace; Wearable Body Sensors;**

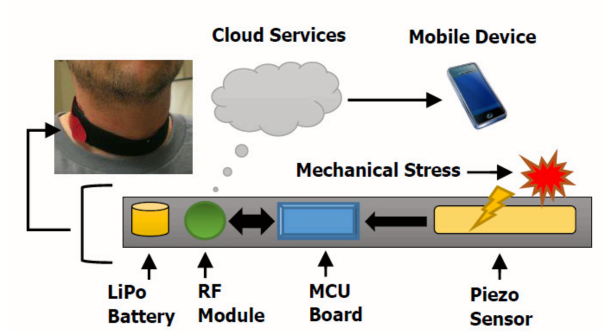

Fig. 1. Systems architecture

I. Motivation and Background

The development and the incorporation of wireless technologies to promote healthy lifestyle behavior, specifically healthy eating and weight control, has the potential to address our ultimate goal of enabling healthier lifestyle choices and behavior modifications needed to prevent obesity and obesity-related diseases [1]. In 2008, medical costs associated with obesity were estimated at $147 billion normal [2]. The Centers for Disease Control (CDC) believes that the best areas for treatment and prevention are monitoring behavior and environment settings.

Studies have shown that the number of swallows during a day correlated more highly with weight gain on the following day than did estimates of caloric intake [3]. This provides motivation for the analysis of food intake patterns based on volume. Many wearable devices have been designed for monitoring activity [4], [5], [6]. However, the focus on automatically inferring eating durations and patterns has been for the most part an unsolved problem. We address this problem by presenting a mobile wearable device which is capable of detecting an individual's eating patterns and determining appropriate health recommendations for the user.

We address the problem of accurately detecting eating patterns by building a non-invasive nutrition and activity monitoring wearable necklace that aids users in preventing weight gain and promoting a balanced healthy lifestyle. Our approach is twofold. First, we propose a system comprising a low-cost sensory necklace with a low-power Bluetooth LE Transceiver, and a smartphone application for receiving sensor data and applying signal processing algorithms. The necklace consists of a microcontroller board with an integrated RF transceiver, a piezoelectric sensor, and a lithium-polymer battery.

Piezoelectric sensors are capable of producing a voltage at their terminals in response to mechanical stress. Thus, the motion of the throat during a swallow is detected using the sensor, and the associated data is transmitted to a mobile application for processing. The mobile application provides a platform through which several algorithms identify swallow events while filtering extraneous noise. Furthermore, these algorithms are able to classify food intake into broad categories of solids and liquids, providing advanced analytics for viewing historic trends, and guiding the users to improve their eating habits based on their chosen goals. The data is then uploaded to a secure cloud server with optional social network integration. Such a system has several crucial benefits including a) increasing user awareness of their food consumption, b) Empowering individuals to establish more regularity and balance in their diets, c) Encouraging users to maintain adequate hydration levels, and d) Giving users the ability to track their historic eating patterns in order to identify changes in their diet. This robust system can empower an individual to self-monitor their eating patterns, while providing feedback and user guidance from the mobile application.

This paper is organized as follows. Section II presents an overview of prior art in the field of food intake monitoring and energy expenditure estimation. Section III describes the hardware architecture, embedded sensors, and Android application. Section IV the algorithms used to detect swallows, followed by the experimental procedure in Section V and results in Section VI.

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II. Related Work

One of the most simple and yet popular ways of monitoring dietary intake is the multi-pass 24-hour dietary recall method, which is based on the data patients provide at the end of a randomly selected day. Each individual gives an oral or written report including the amount and type of food they have eaten during the day, as they recall, which is then used to calculate food intake. This approach measures food intake in a reasonably quantitative manner but with significant error because people don't recall the exact amount of food they have eaten [7]. Experimental data shows that food intake is usually reported with error and measurement variance also depends on the patient's experience with this system [8].

Recent research has been developed that use a watch-like configuration of sensors to track wrist motion throughout the day to automatically detect periods of eating [9]. Results show an accuracy of 81% for detecting eating when compared to manually marked event logs of eating. While this work shows promise, it does not capture people that eat and drink with two hands (92% of food bites with the dominant hand but only 57% of liquid bites), and also has a high false positive rate (one per five bites).

Swallows could also be detected as a sign of food intake. However, current systems detecting swallowing maintain a dependency on bulky and potentially unsafe equipment (video fluoroscopy) and invasiveness (subcutaneous EMG) [10]. Some recent works suggest the use of throat microphones as a means of catching audio signals from throat and extracting swallowing sounds afterwards [11]. In a very promising work by [12], authors analyze bite weight and classify food acoustically from an earpad-mounted sensor. Results show promise, but as other acoustic methods, this system may not be practical in environments with high ambient noise. Analyzing wave shape in time domain [11] or feature extraction and machine learning [13] has resulted in an 86% swallow detection accuracy in an in-lab controlled environment. However, the device is bulky and uncomfortable to wear and effectiveness of the systems in everyday use had not be determined. Our system is wearable, non-invasive, and maintains a low computation load such that it could be implemented on a mobile multi-purpose device and used on a regular basis for day-long periods.

Much of the research related to distinguishing between swallow sounds, vocalization, breathing and other sounds are based on ad-hoc placement of microphones, accelerometers and audio sensors on the neck. Some studies have reached accuracy rates of 91.7% in an in-lab controlled environment using neural networks with false positives of 9.5% [14]. A more recent study using support vector machines have been able to reach swallow detections of up to 96.7% in an in-lab setting [10]. However, these devices are mounted very high up in the top part of the trachea, near the larynx. Such positioning of a device is quite uncomfortable to wear throughout the day.

The work described by Cheng et al. in [15] explores the idea of capacitive sensing for activity recognition. Though inital results are promising, swallow detection for water was not quite as high as classification rates for other activities. However, this is a method worthy of further investigation. Another promising paper by [16] uses a combination of two non-invasive sensors for swallow detection- a microphone, and EMG. This approach requires several EMG sensors placed at several locations around the neck, including the submental EMG position directly below the chin. Results show that a sensor fusion model improves detection accuracy, which motivates additional research in this area. An extended experimental evaluation and additional assessments on user comfort could further increase the practicality of this system.

Our system is the first to use a low cost piezo-electric vibration sensor on the lower neck to detect swallows, and is designed to be comfortably placed in a manner similar to a necklace. Because studies show reduced ability of the body to compensate properly when calories are consumed in liquid form compared to solid form, [17], some health experts now explicitly recommend restrictions on calories consumed in liquid form (e.g., 2007 report by the World Cancer Research Fund [18]. Our system is capable of distinguishing between solid and liquid consumed throughout the day.

Fig. 2. This figure shows one variant of the necklace including the embedded piezoelectric sensor used to detect swallows

III. Hardware and Sensors

In this section, we describe the hardware and software components of our system.

A. Necklace

A piezoelectric sensor, sometimes known as a vibration sensor, produces a voltage when subjected to physical strain. By placing a piezoelectric sensor firmly against the throat, the motion of the skin during a swallow is represented in the output of the sensor, when sampled at frequencies as low as 5 Hz. In this design, one end of the sensor is securely fastened to the necklace, while the other hangs freely. During a swallow event, muscular contractions result in motion of the skin, which pushes the vibration sensor away from the body and towards the fabric of the necklace, generating a unique output voltage pattern, as shown in Figure 3.

Our necklace features a thin, lightweight piezoelectric vibration sensor attached to the inside of the fabric, along with a small microcontroller board capable of sampling the sensor and transmitting the data to a mobile phone via Bluetooth. The hardware is powered by a lightweight lithium-polymer battery.

The necklace is available in several varieties including a sportsband suitable for athletes and other active individuals, and another targeted towards a more fashion-conscious audience. Because the hardware components of the necklace are very compact and lightweight, they can be embedded in several different formfactors. One such design is shown in Figure 2. Because the piezoelectric sensor generates a voltage in response to physical strain, tightening the necklace excessively such that motion is restricted has a negative effect on sensor accuracy; the necklace is designed to be worn loosely and comfortably, but sufficiently tight such that the sensor remains in contact with the skin.

B. Microcontroller Board

The recently released RFDuino board samples the voltage of the vibration sensor at a rate of 20Hz, converting the voltage to a digital signal using the on-chip A/D converter. The data is then buffered and transmitted to a mobile phone. This Arduino-compatible board is easily programmed, very compact, and features a Bluetooth 4.0 LE transceiver on-board, based on the RFD22301 SMT module. The embedded processor is an ARM Cortex M0 with 256kB of flash memory and 16kB of RAM.

C. Android Application

This system includes a mobile phone application for data reporting and visualization. The application displays the estimated volume of the current meal, as well as the daily total. A reporting tool displays alerts to the user if any unusual eating habits are detected. These anomalies include, but are not limited to:

a) Cases in which a meal is found to be substantially larger than the recent average for that time of day

b) Cases in which the time interval between meals is excessively large, or excessively small

c) Periods in which excessive snacking is taking place throughout the day

d) An extensive period of time in which liquids are not consumed, possibly suggesting dehydration

The algorithm is also able to perform a basic classification of food types into broad categories of solids and liquids, allowing users to ensure basic nutritional balance in their diet.

The mobile application uses the Bluetooth 4.0 LE protocol to receive data from the necklace while maximizing battery life. The data is then processed for swallow identification, classification, and analytics. Lastly, all collected and processed data is uploaded to a secured cloud server for patient tracking and statistical analysis.

IV. Algorithm Design

This wearable system includes several algorithms for detecting swallows, and classifying between solid and liquid intake.

Algorithm 1: Swallow Detection Algorithm

```
Smooth(Data);
for i = 1:Window:Size(Data) do
    avg = CalculateAverage(Data[i]:Data[i+Window]);
    for j = i:i+Window do
        diff = abs(avg - Data[i])
        if diff < threshold then
            diff = 0;
        else
            data[i] = diff;
for i = 1:Size(Data) do
    if Data[i] > 0 then
        SwCount++;
        i = i + Jump;
```

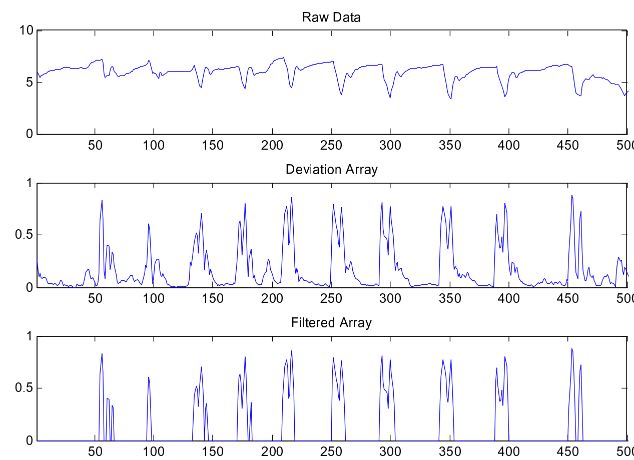

Fig. 3. This figure describes how the original sensor data is processed into a form in which swallows are easily detectable. Raw data (top) is sampled from the piezoelectric sensor, and a smoothing function is applied. Then, a sliding window is used to compute the standard deviation of the data set (center). After more smoothing and filtering, a thresholding technique is applied (bottom) and the peaks are identified.

A. Swallow Identification

Figure 1 describes a simplified version of the algorithm implemented on the mobile phone, which is used to detect swallows based on data from the vibration sensor received via Bluetooth. The algorithm calculates the standard deviation of the dataset by means of a sliding window, and applies a thresholding technique to identify swallows.

Figure 3 illustrates the general signal processing flow. The top figure is the raw waveform acquired from the vibration sensor over time, at a rate of 20Hz. The noticable dips in the waveform generally correspond with swallows. The data is then smoothed, to reduce the impact of oscillations and noise that are unrelated to swallowing. Subsequently, a sliding window is applied. Within each window, the average voltage from the vibration sensor is calculated. Subsequently, the standard deviation of each point within the window is calculated. This

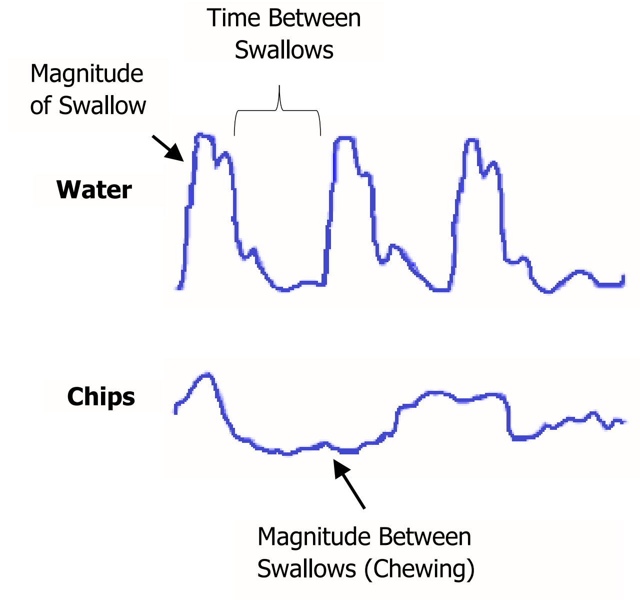

Fig. 4. Several features are used to classify between solid and liquid foods. The strongest heuristic is the detection of chewing inbetween swallows, as indicated by the relatively shallow troughs visible in the bottom waveform, compared to the more prominent spikes associated with liquid consumption noticable in the top waveform.

is necessary because occasionally, swallows correspond with increases in voltage rather than decreases as shown in Figure3. Finally, all points in the standard deviation waveform which do not exceed a certain threshold are zeroed, resulting in the final waveform. This step is necessary because minor spikes are generally the result of neck or torso movement, and are unrelated to food intake. The final step in swallow detection is to count the number of peaks in the waveform, followed by a period of disabled detection after each swallow to ”debounce” the sensor from false-positives. This is required since several consecutive spikes in rapid succession are typically the result of the same swallow.

V. Classification

Because the piezoelectric sensor is capable of detecting motions beyond swallows, the detection of consistent chewing inbetween swallows is a reliable indicator that a solid food is being consumed, while several swallows (especially if they are in rapid succession) with no chewing detected inbetween may indicate that a liquid is being consumed.

Figure 4 illustrates several features which can be used to differentiate solid and liquid foods, by comparing waveforms corresponding to a glass of water (top) and chips (bottom). The most critical indictator that the food being consumed is a liquid is the absense of vibrations corresponding with chewing, inbetween swallows. However, swallows corresponding with liquid foods are typically sharper and higher in magnitude. Furthermore, a very large amount of swallows in a short timeframe are indicative of liquids, since most dry foods require much more chewing before they can be swallowed. The detection of chewing between swallows is by far the most important heuristic, since variations in eating style and pace limit the usefulness of the other two features. The relationship of standard deviation between swallows (which is indicative of chewing), and food type, is shown in Figure 5. As this figure shows, intervals inbetween swallows typically have much higher standard deviations for solid foods, compared to liquids.

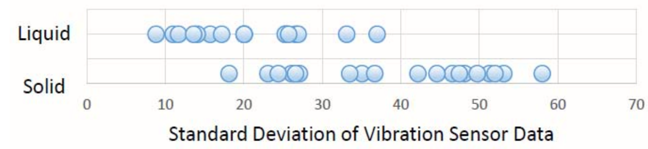

Fig. 5. This figure shows the standard deviation of vibration sensor data between swallows, for both solid and liquid foods. This heuristic is critical for classification between these two food types, as the disturbance caused by chewing is not present in the liquid waveform.

VI. Experimental Procedure

A. Data Collection

Data was collected from ten subjects. Each subject consumed two types of food- a sandwich on white bread, and several potato chips. These foods were specifically chosen to represent a wide variety of textures, ranging from crunchy to chewy. Furthermore, each subject consumed a small glass of water, to create a dataset to support the design of an algorithm for classifying solid vs. liquid foods.

For each subject and each food type, the piezoelectric sensor was placed in six different locations on the throat. This was necessary to identify the regions of the neck which produced the most clear signal. Furthermore, the sports band on which the sensor was mounted ranged from loose to firm.

It is necessary to evaluate the strength of the correlation between portion size and number of swallows necessary to consume a food item. Therefore, a similar experiment was conducted in which each subject consumed a small sandwich, a large sandwich, and two cups of water (small and large). In every case, the large sandwich was exacty double the size of the small sandwich, and contained the exact same ingredients. Similarly, the large cup of water was exactly double the volume of the small cup. It was necessary to determine if doubling the portion size consistently resulted in a proportional increase in number of swallows.

VII. Evaluation

A. Portion Sizes vs. Swallow Count

Table I shows the relationship between portion size and number of swallows, which confirms our initial assumptions that there is a roughly linear relationship which relates swallow count to food volume. A small cup of water (8oz) requires half as many swallows compared to a large cup of water (16oz), and the same relationship holds for small sandwiches (3 inch) compared to large (6 inch) with several exceptions.

TABLE I
SWALLOW COUNT VS. PORTION SIZE

ID	Sandwich (S)	Sandwich (L)	Water (S)	Water (L)
1	11	19	8	13
2	9	21	7	13
3	9	25	11	21
4	25	48	8	12
5	15	38	17	45
6	13	29	12	19
7	9	32	9	18
8	22	41	13	33
9	15	30	21	28
10	8	23	9	23

However, the large variance between subjects implies that calibration to an individual's personal eating style is crucial to the practicality of this system.

B. Detection of Swallows

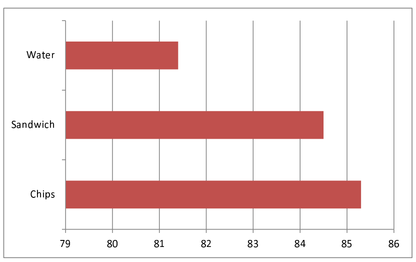

Fig. 6. Accuracy of detection by food type (in percent)

		Predicted Class		
		Solid	Liquid	Precision
Actual	Solid	14	3	0.823
	Liquid	2	15	0.881
	Recall	0.875	0.833	

Fig. 7. Accuracy of classification by food type

Figure 6 illustrates the accuracy of swallow detection for three different food types. The percentage accuracy for chips, water, and sandwiches were 85.3%, 81.4%, and 84.5%, respectively.

C. Classification

Figure 7 shows the accuracy of classification between solid and liquid foods. A naive Bayes classifier was used, resulting in an F-Measure for solids and liquids of 85% and 86%, respectively.

D. Sensor Placement

It was determined through extensive experimentation that the accuracy of swallow detection increases substantially as the sensor is moved toward the lower region of the throat, compared to the mid-throat and the upper region, as shown in Figure 8. Figure 8 shows the relative accuracy of swallow detection with respect to the location of the neck on which the vibration sensor was placed, based on data collected from ten subjects.

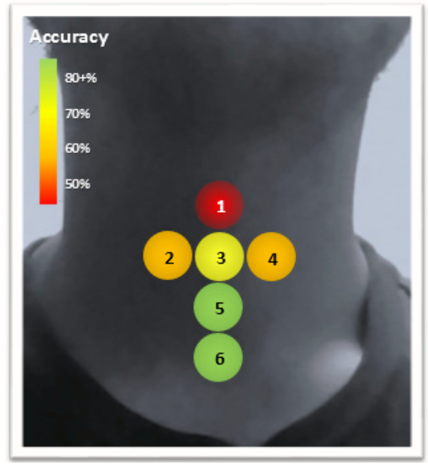

Fig. 8. The relative accuracy of swallow detection increases significantly as the piezoelectric sensor is moved towards the lower part of the neck. Accuracy is also maximized when the sensor is placed in a horizontally centered orientation.

E. Sensor Band Tightness

Figure 9 shows vibration sensor waveforms for three configurations: comfortable, tight, and loose. Typically the loose configuration allowed only intermittent contact between the vibration sensor and neck. The tight configuration was typically described as too uncomfortable to be worn for more than a few minutes at a time.

The waveforms reveal that tightening the necklace restricts the movement of the piezo sensor, and decreases the sensitivity of detection such that swallows are barely visible on the waveform. Furthermore, the loose configuration's lack of movement restriction causes significant fluctuation in the data which was rendered unusable. Experiments reveal that the necklace must be fastened for the piezoelectric sensor to typically remain in contact with the skin, but sufficiently loose such that its movement is not completely restricted by the tension of the sports band.

F. Impact of Head and Body Movements

Several movements not associated with eating or drinking can produce distinct waveforms, as shown in Figure 10. The first observation is that abrupt vertical and horizontal head movements can potentially register as swallows. However, the waveform reveals a much more irregular pattern than the data associated with beverage consumption, which implies that these motions can be detected and filtered out. In our experimentation, 10% of horizontal head movements were

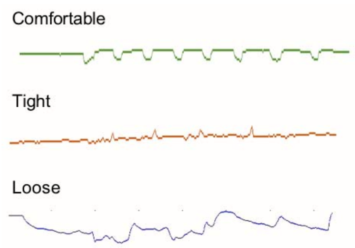

Fig. 9. This figure shows the impact of necklace tightness on the clarity of the signal.

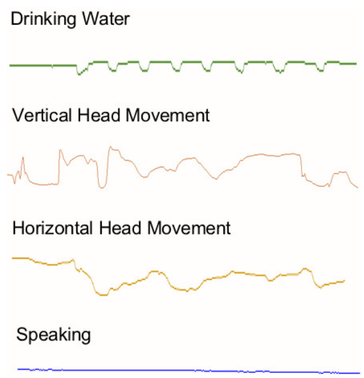

Fig. 10. This figure shows the representative signal of various movements not associated with ingestion.

detected as swallows, while approximately 15% of abrupt vertical head movements were detected as swallows.

VIII. Future Work

Though the system attempts to identify the volume of food consumption and make users more aware of their eating habits, the next logical step is to extend the classification of food types into several broad categories. This may require supplementing the hardware with additional sensors such as a small microphone. Another potential improvement is to extend the system with fully real-time functionality. In the current system, data is transmitted from the necklace in real-time, and instant feedback is given to the user when a swallow is detected. However, the more advanced classification algorithms which distinguish between different food types are implemented offline.

IX. Conclusion

In this paper, we describe a low-cost, wearable sensor system in the form of a necklace with an embedded piezoelectric sensor. The necklace is capable of estimating volume of food consumption and transmitting the data to a mobile phone for analysis. The system was able to detect 85.3% of potato chip swallows, 84.5% of sandwich swallows, and 81.4% of water swallows. Furthermore, the system is capable of identifying solid and liquid foods with an average F-measure of 86%. The system and software described in this paper were designed with the primary goal of making individuals more aware of their eating habits, which we believe is critical for weight loss.

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